

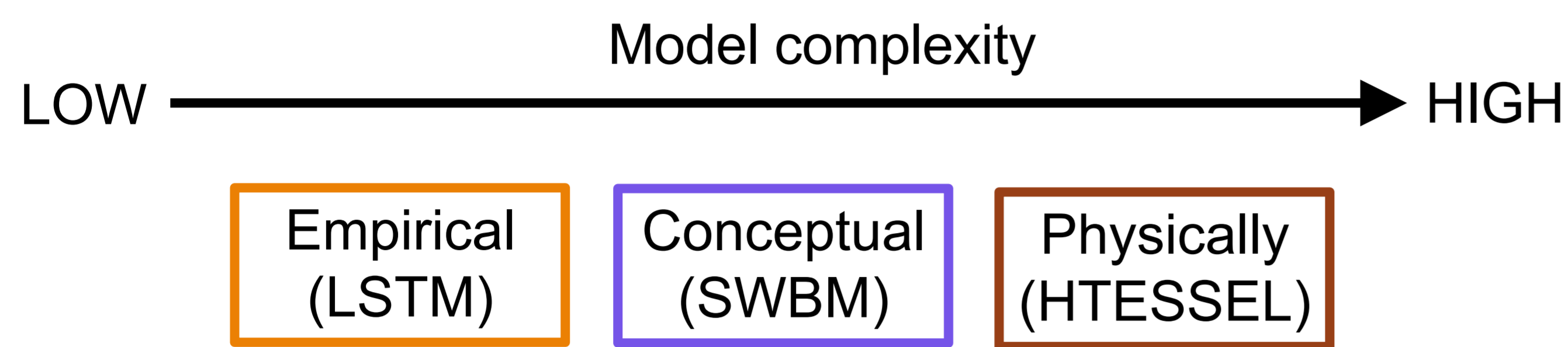
How can deep-learning assist physical modeling and forecasting?



MAX-PLANCK-GESELLSCHAFT

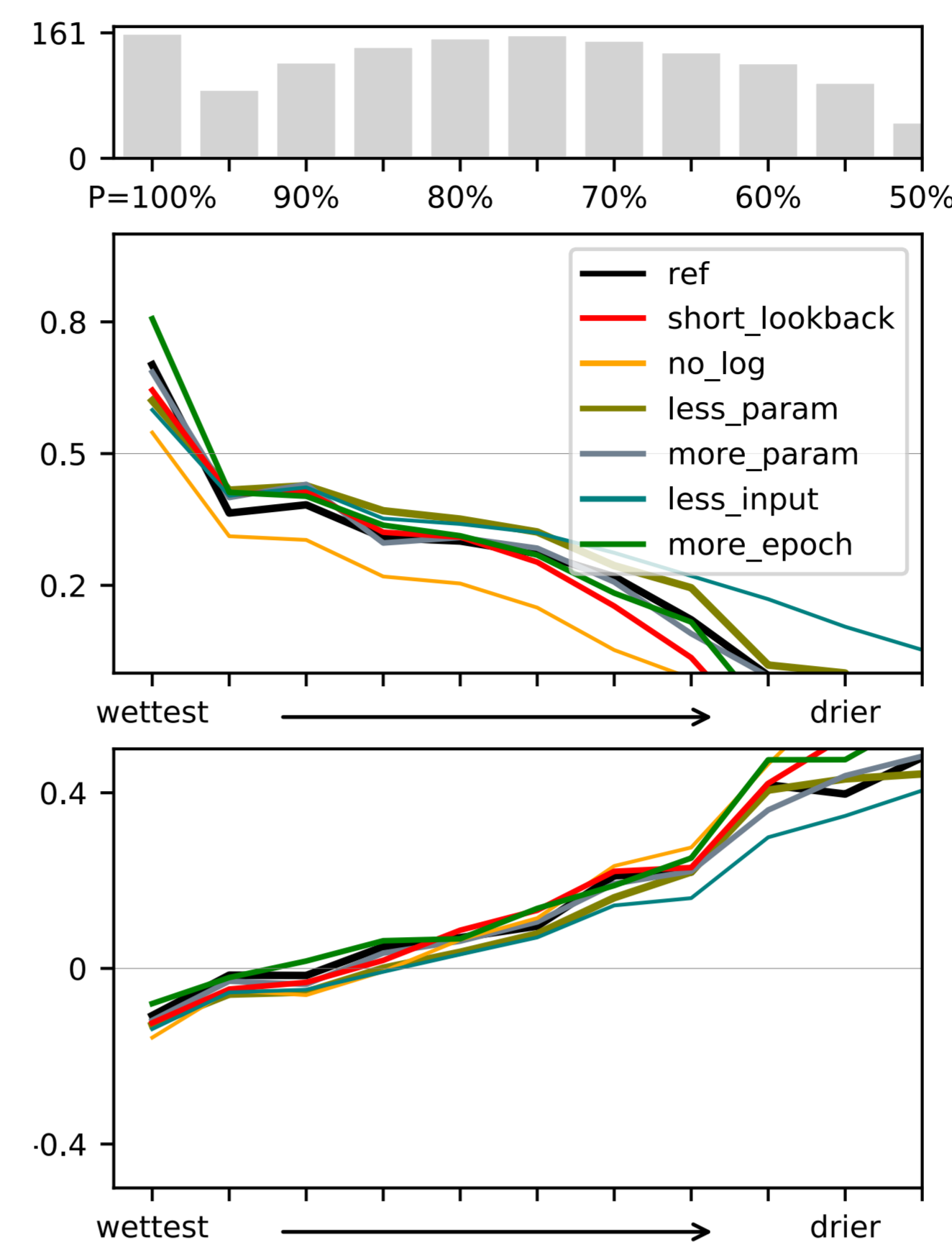
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Q1. How reliable are land surface models (LSMs) under a changing climate?



Calibration to the wettest year vs. Evaluation over the remaining years using 24-years streamflow data from 161 catchments in Europe

Q2. How can machine-learning techniques assist hydro-meteorological forecasting?

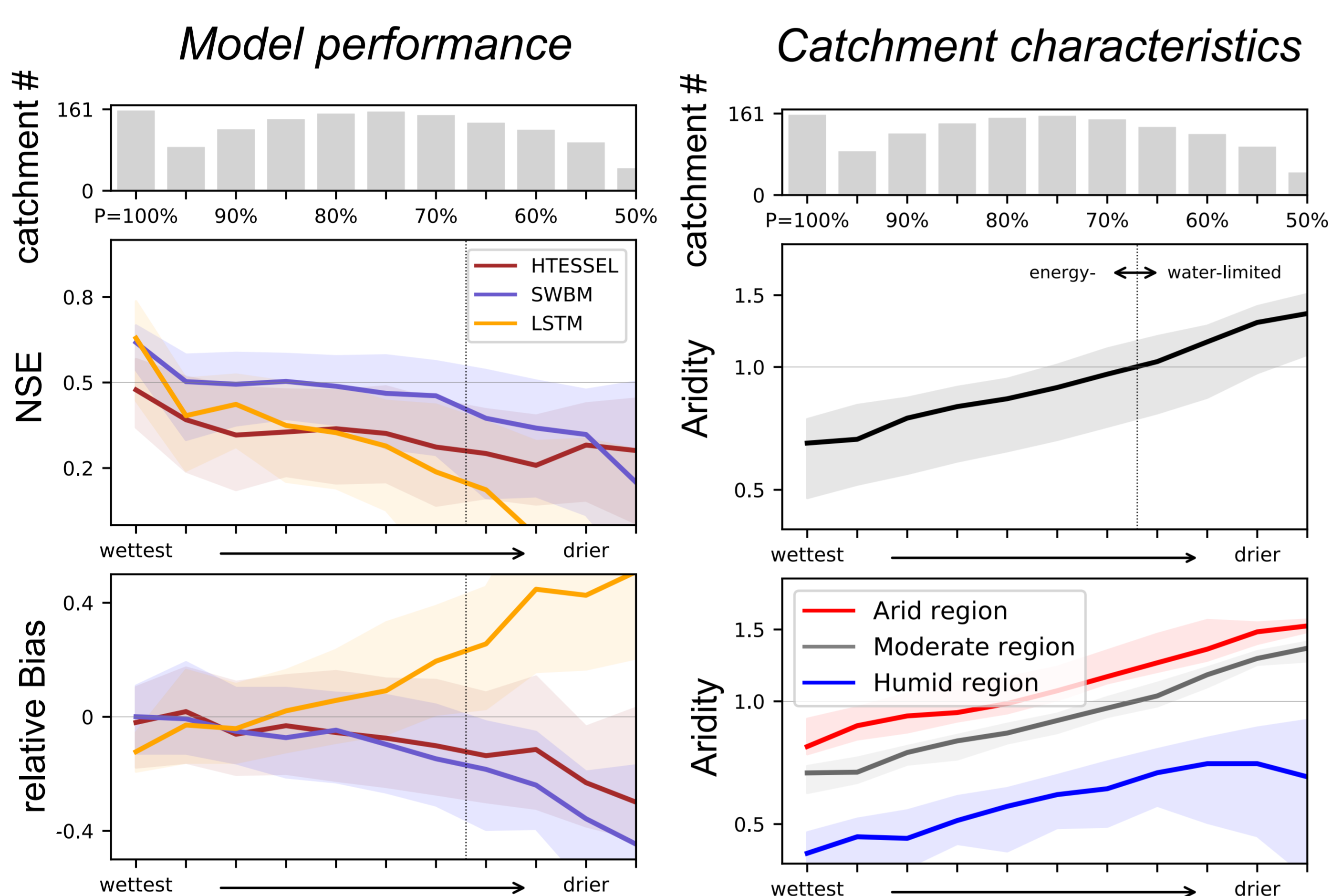


Long Short-Term Memory (LSTM)

General conclusions remain the same, however, certain hyperparameters play a relatively larger role in determining the robustness of model performance

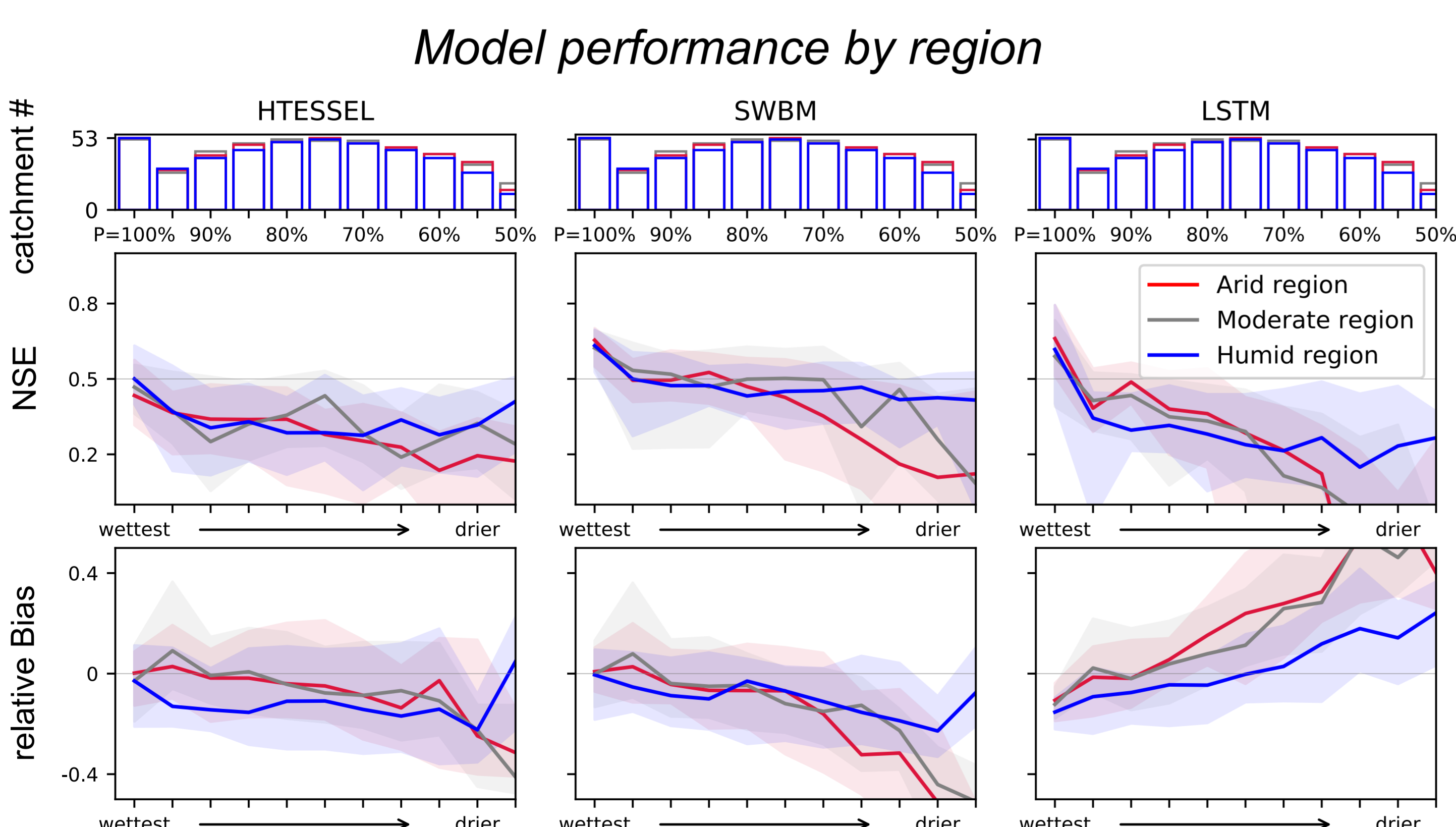
=> **what is the optimal model set-ups for specific hydrologic applications?**

1. Process-based models show comparatively robust performance under changing conditions



- Models have difficulties in representing hydro-climatic regime shifts; e.g., energy- to water-limited conditions
- Relatively robust performance of the most complex model, HTESSEL, highlights the need for further improved and expanded process representations in current models.

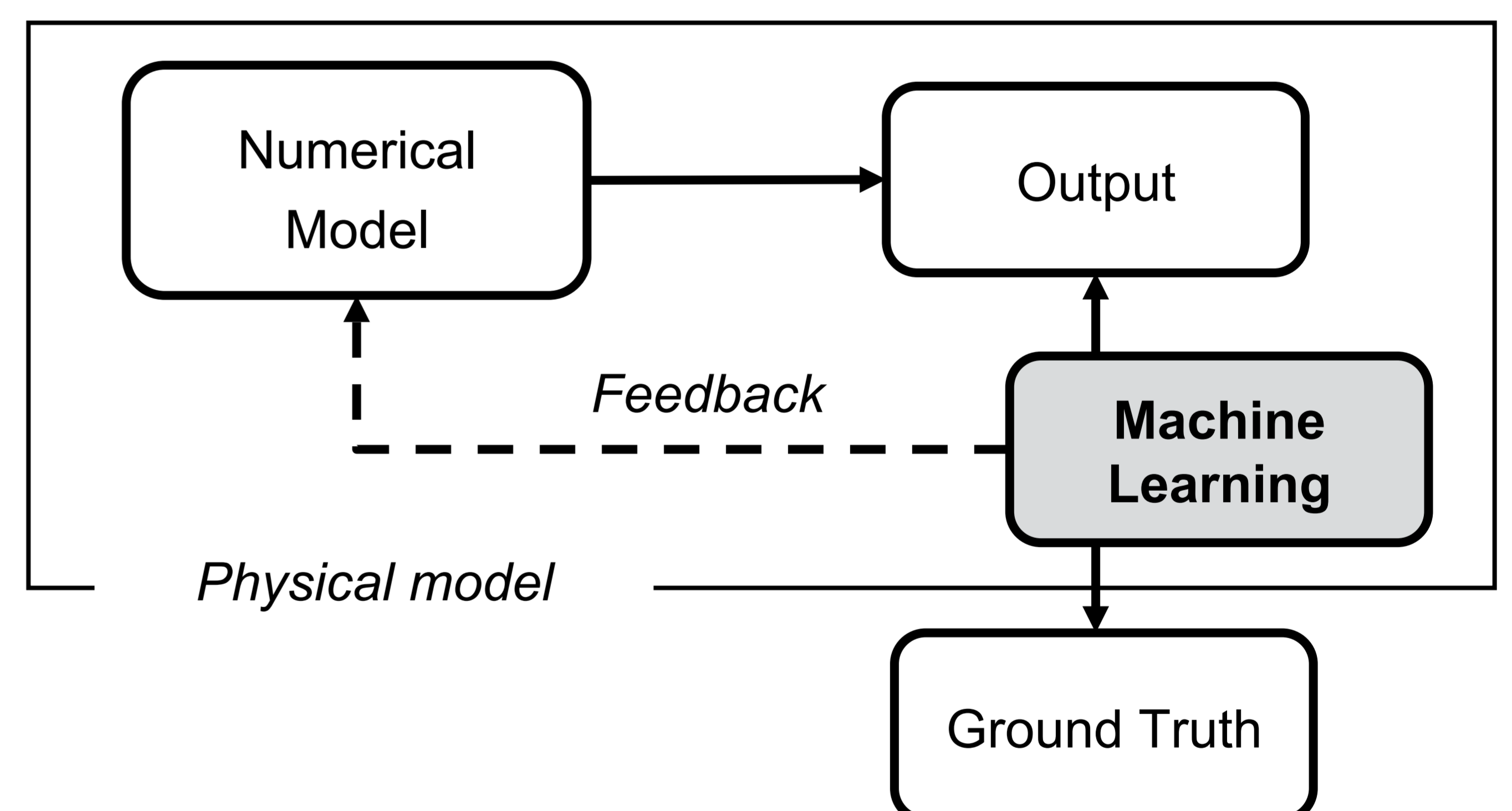
2. Models show faster performance decline in arid regions



- Potential difficulties in LSM predictions are found in semi-arid regions, where a regime change between energy- and water-limited conditions is expected.

Work Plan 1: Post-processing of weather forecasts with machine-learning techniques

- Machine-Learning can learn patterns of model-observation mismatch and correct biases in physical model outputs.
- It can also improve understanding of model weaknesses, e.g., through sensitivity analysis to determine the patterns in model errors.



Work Plan 2: Generating gridded soil moisture data from a machine learning-based data-driven model

- A data-driven model will be developed and its extrapolation capacity will be investigated, to generate spatio-temporal soil moisture fields from point measurements.

